Decoding the neural drive to muscles from the surface electromyogram.

Decoding the neural drive to muscles from the surface electromyogram

Dario Farina [a,*], Aleš Holobar [b,c], Roberto Merletti [b], Roger M. Enoka [d]

[a] Center for Sensory-Motor Interaction (SMI), Department of Health Science and Technology, Aalborg University, Aalborg, Denmark
[b] Laboratory for Engineering of the Neuromuscular System, Department of Electronics, Politecnico di Torino, Torino, Italy
[c] Faculty of Electrical Engineering and Computer Science, University of Maribor, Maribor, Slovenia
[d] Department of Integrative Physiology, University of Colorado at Boulder, CO, USA

A B S T R A C T

This brief review discusses the methods used to estimate the neural drive to muscles from the surface electromyogram (EMG). Surface EMG has been classically used to infer the neural activation of muscle by associating its amplitude with the number of action potentials discharged by a population of motor neurons. Although this approach is valuable in some applications, the amplitude of the surface EMG is only a crude indicator of the neural drive to muscle. More advanced methods are now available to estimate the neural drive to muscle from the surface EMG. These approaches identify the discharge times of a few motor units by decomposing the EMG signal to determine the relative changes in neural activation. This approach is reliable in several conditions and muscles for isometric contractions of moderate force, but is limited to the few superficial units that can be identified in the recordings.

Contents

1. Introduction

The central nervous system controls the force generated by a muscle with recruitment of motor units and adjustments in their discharge rates (Adrian and Bronk, 1929). The number of action potentials discharged by the motor neurons innervating the muscle constitutes the neural drive from the spinal cord to the muscle. Due to a high safety margin at the nerve–muscle synapse, action potentials discharged by the motor neurons usually emerge as action potentials that propagate along the muscle fibers. Thus, the ensemble of electrical activity generated by a muscle is strongly associated with the magnitude of the motor command discharged by the motor neuron pool.

The electrical activity in muscle can be recorded with electrodes placed over the skin. The resulting surface electromyogram (EMG) is the sum of the action potentials generated by the motor units and filtered by the volume conductor. The shape of each motor unit action potential depends on the number and anatomical characteristics of the innervated muscle fibers, and on the properties of the recording electrodes (Farina et al., 2002). The magnitude of the neural drive to muscle can be quantified from the surface EMG by identifying the number of motor unit action potentials generated per time unit.

Although the amplitude of the surface EMG is often used to estimate the magnitude of the neural activation sent to muscle, there are some limitations to this interpretation. First, the size of a motor unit action potential at the surface of the skin is only partly related to motor neuron size (Keenan et al., 2006). Second, the relative

* Corresponding author. Address: Center for Sensory-Motor Interaction (SMI), Department of Health Science and Technology, Aalborg University, Fredrik Bajers Vej 7 D-3, DK-9220 Aalborg, Denmark. Tel.: +45 96358821; fax: +45 98154008.
E-mail address: df@hst.aau.dk (D. Farina).

contribution of an action potential to the amplitude of the EMG signal may differ across conditions (Dimitrova and Dimitrov, 2003). To circumvent these limitations, an alternative approach is to use the times of occurrence (discharge times) of the action potentials of individual motor units, identified by surface EMG decomposition, to estimate the motor output from the spinal cord.

This brief review discusses the methods used to estimate the neural drive to muscles from the surface EMG. As detailed issues related to classic approaches were reviewed previously (Farina et al., 2004a), this review focuses on recent developments in interpreting surface EMG amplitude and in decomposing the surface EMG to detect discharge times.

2. Amplitude of the surface EMG

The amplitude of the surface EMG is usually estimated as the standard deviation of the signal (Clancy and Hogan, 1994). The average rectified value (ARV) and the root mean square (RMS) values of the surface EMG are optimal estimators of amplitude when the EMG signal follows Laplacian and Gaussian distributions, respectively (Clancy and Hogan, 1999). These two estimators are equivalent in practical applications (Clancy et al., 2002). The use of signal amplitude as an indicator of the neural activation has two major drawbacks. First, the size of surface action potentials differs among motor units and across conditions, which alters the association between number of motor neuron discharges and signal amplitude. Second, the sum of the surface action potentials is less than the sum of the amplitudes of the individual potentials, a phenomenon that has been termed "amplitude cancellation" (Day and Hulliger, 2001; Keenan et al., 2005), which results in the amplitude of the surface EMG underestimating the magnitude of the motor output from the spinal cord and disrupts the association between changes in the two signals.

The variability in action potential size among motor units and across conditions has been analyzed in several studies (Farina et al., 2002; Dimitrova and Dimitrov, 2003; Dimitrov et al., 2008). It seems that the size of a surface action potential is only moderately associated with the size of the motor unit (Keenan et al., 2006) and that, conversely, the size depends on factors that are difficult to control or limit in experimental conditions (e.g., the thickness of the subcutaneous layer; Dimitrov et al., 2002). Thus, the set of surface action potentials that represent the activity of a population of motor neurons has a broad distribution of sizes, which differs among subjects, conditions, and muscles. The absolute EMG amplitude (without normalization), therefore, provides a poor index of the neural drive to the muscle and absolute comparisons are not appropriate (Dimitrova and Dimitrov, 2003). Rather, the surface EMG amplitude should be normalized to a value obtained in a reference contraction, such as a maximal voluntary contraction (Keenan et al., 2005; Yang and Winter, 1984).

Due to amplitude cancellation of motor unit action potentials in surface EMG recordings, the relation between surface EMG amplitude and number of action potentials per time unit would not be linear even if all the action potentials had the same size (Farina et al., 2004a; Keenan et al., 2005). Amplitude cancellation negatively impacts the association between fluctuations in surface EMG amplitude and muscle force. Fig. 1 shows that small changes in the neural drive to the abductor digiti minimi muscle at low contraction forces, as estimated by counting the number of action potentials discharged by nine motor units per unit time (Fig. 1B), were strongly correlated with the exerted force ($R = 0.88$; Fig. 1C) but not with the surface EMG amplitude ($R = 0.21$; Fig. 1D). Also, there was a weak correlation between surface EMG amplitude and force ($R = 0.28$). This example indicates that the amplitude of the surface EMG provides only a crude measure of the changes in neural activation.

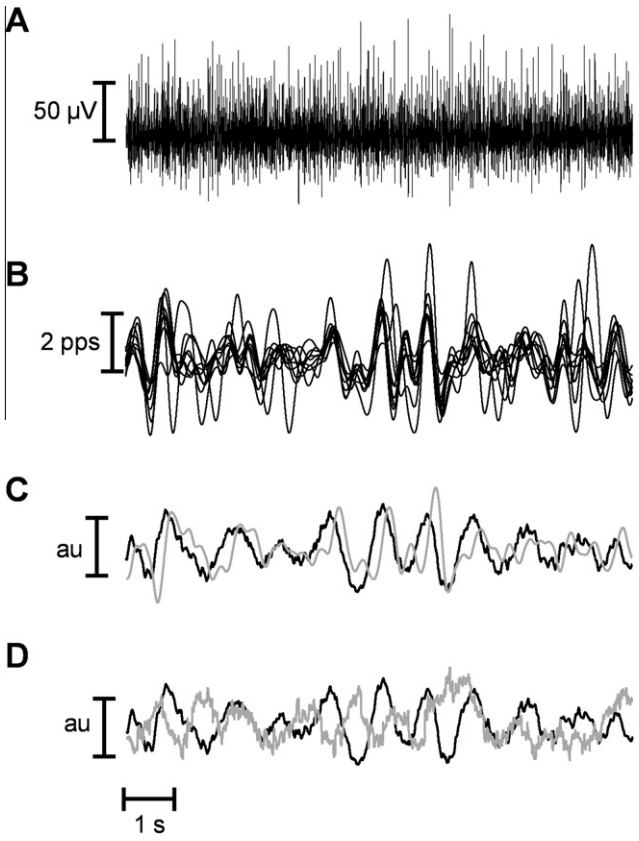

Fig. 1. (A) Surface EMG signal detected from the abductor digiti minimi muscle of a healthy man during an isometric contraction of 10 s duration at 10% of the maximal force. Intramuscular EMG signals were concurrently recorded with two pairs of wire electrodes and single motor unit action potentials were identified by decomposition (McGill et al. 2005). (B) Smoothed discharge rates were obtained by filtering the point process representing the inverse of the interspike intervals (high-pass filtered with cut-off frequency 0.75 Hz and smoothed with Hann window of 400 ms duration) of the motor units identified from the intramuscular recordings ($n = 9$ motor units). The neural activation was estimated by counting the total number of action potentials discharged by the 9 units in each 400 ms interval. (C) Comparison between the abduction force exerted by the little finger during the contraction (grey line) and the neural activation estimated from the count of the number of action potentials in each 400 ms interval (black line) after removing the offset in the two signals. (D) Comparison between the estimated neural activation from panel B (black line) and the amplitude of the surface EMG (grey line). The amplitude of the surface EMG was estimated as the root mean square value in the same intervals used for estimating the neural activation (400 ms in duration). au, Arbitrary units; pps, pulses per second.

The amount of amplitude cancellation experienced by individual action potentials can be predicted analytically (Farina et al., 2008a). It is greater for small potentials and increases as the amplitude of the interference signal increases (Farina et al., 2008a). Because low-threshold motor units tend to produce smaller surface action potentials than high-threshold units (Keenan et al., 2006), it is the surface action potentials of the low-threshold motor units that are reduced more by amplitude cancellation, especially for high levels of muscle activity. As a consequence of this effect, the surface EMG amplitude can be relatively insensitive to changes in the activity of low-threshold motor units. For example, Mottram et al. (2005) found that the discharge rate of low-threshold motor units decreased more rapidly during one type of fatiguing contraction compared with another type, whereas the change in the amplitude of the surface EMG was similar during the two tasks. Similarly, indexes of neural drive to the muscle based on EMG amplitude, such as the neuromuscular efficiency (Deschenes

et al., 2002), are largely biased toward changes in the activity of high-threshold motor units due to the influence of amplitude cancellation.

The amount of amplitude cancellation may vary during fatiguing contractions due to changes in the interference EMG amplitude and the shapes of the motor unit action potentials. When an individual sustains a submaximal contraction, the amplitude of the surface EMG usually increases due to the recruitment of additional motor units (Garland et al., 1994; Person and Kudina, 1972; Riley et al., 2008), the decrease in muscle fiber conduction velocities (Bigland-Ritchie et al., 1981; Merletti et al., 1990), and changes in the shapes of the intracellular action potentials (Dimitrova and Dimitrov, 2002; Hanson and Persson, 1971). The adjustments that occur during fatiguing contractions change the distribution of action potential size and the amount of amplitude cancellation, which alters the relation between the neural activation of muscle and surface EMG amplitude, even when this is normalized.

Fig. 2 shows a simulation analysis that exemplifies the limitations of surface EMG amplitude as a measure of neural activation during sustained contractions. In this example, a population of motor neurons was activated (Fuglevand et al., 1993) to sustain contractions at 30% and 60% of the maximal voluntary contraction (MVC) force until task failure, which corresponded to a decrease in simulated force by 2% MVC force for more than 2 s. The contractile properties, recruitment, and discharge characteristics of the motor units changed in response to the simulated accumulation of metabolites, according to a model of the intra- and extra-cellular compartments (Dideriksen et al., 2009). Surface EMG action potentials were generated by a validated model (Farina et al., 2004b). The time to task failure in these simulations was 293 s for 30% MVC and 79 s for 60% MVC (Fig. 2A).

The number of action potentials discharged each second by all active motor units (expressed as % of the number during an MVC) increased from 28% at the beginning of the contraction to 61% at the end (30% MVC force) and from 52% to 62% (60% MVC force) (Fig. 2C). This increase was due to the recruitment of additional motor units during the contraction. Although the number of action potentials per time unit was greater at the beginning of the stronger contraction (52% vs. 28%), it was similar at task failure for the two tasks. The surface EMG amplitude (RMS) at task failure was 62% and 88% of the MVC value for the 30% MVC and 60% MVC contractions, respectively (Fig. 2D), despite a similar number of action potentials discharged per second. This discrepancy indicates that the relative changes in surface EMG amplitude during the simulated contraction failed to represent some significant changes in the neural drive. The dissociation between the changes in EMG amplitude and number of discharged action potentials were partly due to differences in the amount of amplitude cancellation (Fig. 2E). Amplitude cancellation was similar at the beginning of the tasks (30% and 31%, respectively) but increased more for the

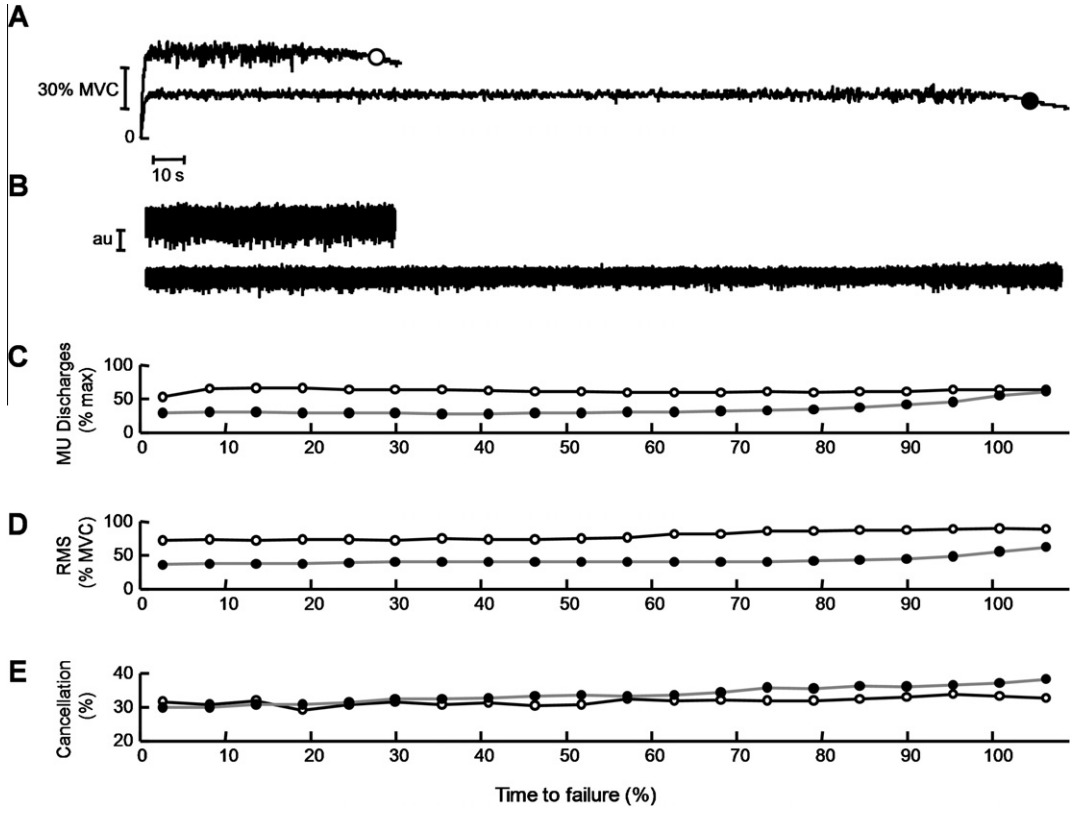

Fig. 2. (A) Simulated forces during contractions at 30% and 60% of the maximal voluntary contraction (MVC) force. The open (60% MVC) and filled (30% MVC) circles indicate the times of task failure for the two contractions, which was defined at the time when the force decreased by 2% MVC force for 2 s. The simulations represent contractions with the first dorsal interosseus muscle. The number of motor units in the muscle was 120 and the upper limit of recruitment in the absence of fatigue was ~60% MVC force. The other model parameters at the beginning of the tasks were similar to those described by Keenan et al. (2005); however, the parameters changed over time to simulate the adjustments that occur during fatiguing contractions (Dideriksen et al., 2009). (B) The simulated surface EMG signals during the two contractions. Motor unit action potentials were generated with the EMG model proposed by Farina et al. (2004b). (C) The total number of discharges of all active motor units, expressed as a percentage of the number of discharges during an MVC contraction for the 30% MVC (filled circles) and the 60% MVC (open circles) tasks. The number of discharges was computed for time intervals corresponding to 5% of the time to failure for each task. (D) The root mean square (RMS) value of the surface EMG signal computed for the same time intervals as in (C). (E) The amount of amplitude cancellation in the simulated surface EMG signals for the same time intervals as in (C) and (D). Amplitude cancellation was computed as the difference in the amplitudes of the rectified and summed action potential trains (Keenan et al., 2005), which is only possible in simulated conditions. au, Arbitrary units; MU, motor unit.

30% MVC (38% at task failure) than for the 60% MVC task (32% at task failure). Although different trends in EMG amplitude can be obtained by choosing other model parameters, this example indicates that changes in surface EMG amplitude provide a poor index of the modulation in neural activation during sustained contractions.

3. Decomposition

The main issue when using EMG amplitude to estimate the neural drive to muscles is the influence of differences in action potential shape on the composite signal. The use of EMG amplitude for this purpose, however, assumes that the distribution of action potential shapes does not have a significant influence on the results, but this is not correct. In contrast, identification of the times at which action potentials are discharged by individual motor units from the interference EMG allows more direct access to the neural coding. The procedure to determine the discharge times is referred to as decomposition of the EMG signal (De Luca et al., 2006).

The classic approach to identifying motor unit action potentials is based on intramuscular EMG signals (Adrian and Bronk, 1929) as they provide greater selectivity than surface EMG signals. Recent advances, however, have developed the option of decomposing the surface EMG into its constituent motor unit action potentials (Holobar et al., 2009; see Merletti et al. (2008) for a review). Decomposition involves compensating for the shapes of the action potentials and identifying the underlying trains of motor unit action potentials (Holobar and Zazula, 2007). Contrary to simpler approaches (Kallenberg and Hermens, 2006), the methodology requires distinguishing the action potentials of different motor units, which is facilitated by recording the surface EMG from several locations over the muscle (Farina et al., 2008b; Fig. 3). These "high-density surface EMG" systems (Blok et al., 2002; Merletti et al., 2008) comprise several, closely spaced surface electrodes.

Fig. 3B shows the amplitude distribution of surface EMG signals recorded by 61 electrodes, from which 56 bipolar derivations were obtained, at one instant in time. The amplitude values were determined from the action potentials of the motor units that were active at that instant. The amplitude distributions of the motor unit potentials that contributed to the interference signal at the indicated instant were obtained with a decomposition method (Holobar and Zazula, 2007). The sum of the motor unit amplitude distributions (Fig. 3C) corresponds to the amplitude of the interference signal (Fig. 3B) with small error. These associations are valid for all other time instants and allow unequivocal identification of the motor unit discharge times as the initiation of the corresponding action potentials (decomposition of the signal). Conversely, the amplitude values of the interference signal recorded from only a

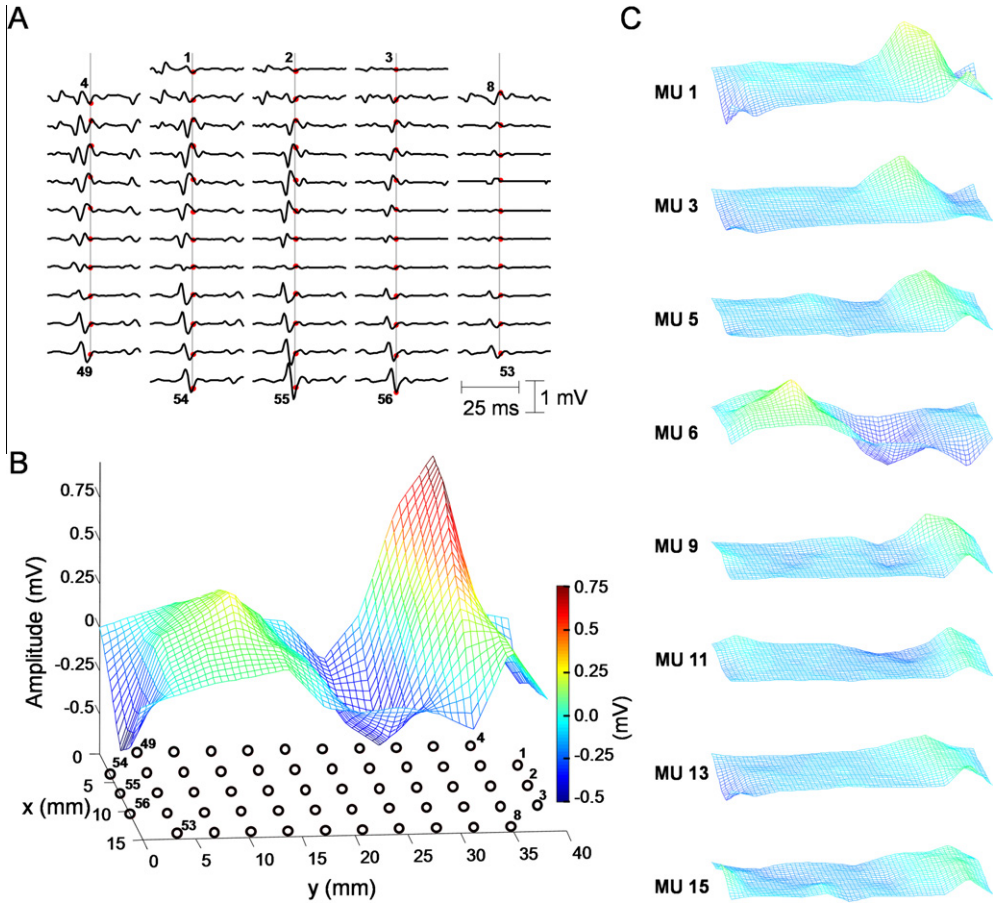

Fig. 3. (A) Surface EMG signals recorded from the abductor pollicis brevis muscle of a healthy man during an isometric contraction sustained at 10% of the maximal voluntary contraction (MVC) force. The signals were detected as bipolar recordings from an electrode grid of five columns and 13 rows (with four missing electrodes at the corners; 56 bipolar recordings; 5 mm interelectrode distance), with the columns aligned along the fiber direction. (B) Amplitude of the multi-channel EMG recording for all electrode locations at the instant indicated by the small dots and vertical lines in (A). Some of the recording locations are indicated by numbers corresponding to those in (A). The multi-channel surface EMG signal was decomposed (Holobar and Zazula, 2007) to identify 18 motor units. Eight of the 18 motor units had action potentials at the instant indicated in (A) and these contributed to the amplitude of the interference EMG signal at that instant. (C) The amplitude of the action potentials of the eight motor units at the instant indicated in (A). The amplitude distribution of the interference signal shown in (B) corresponds closely to the sum of the amplitude distributions in (C). The colorbar is common to all amplitude maps. MU, motor unit.

few electrode locations can be described by multiple combinations of motor unit action potentials, thus the decomposition would have multiple solutions (Farina et al., 2008b).

Among the methods developed for decomposing the surface EMG, the convolution kernel compensation (CKC) technique (Holobar and Zazula, 2007) has been extensively validated with both simulated and experimental signals (Holobar et al., 2009). Fig. 4 shows an example of this procedure for experimental signals recorded with a high-density surface EMG system from the biceps brachii muscle. Each motor unit is represented by its template action potential in terms of its shape and location (Fig. 4C). The shapes of the action potentials usually differ across motor units due to the high-density EMG recording (Farina et al., 2008b). Even when action potentials of two different motor units have similar shapes on most of the multi-channel recordings (e.g., motor units 2 and 8 in Fig 4C), the small but consistent differences on some of the other channels allow the decomposition of the multi-channel EMG to discriminate between the two motor units. The example shown in Fig. 4 presents the discharge times of motor unit action potentials identified during a ramp contraction so that the recruitment thresholds of the motor units could be estimated (Farina et al., 2009).

A comparison of decomposition results from concurrently recorded intramuscular (assumed gold standard) and surface EMG

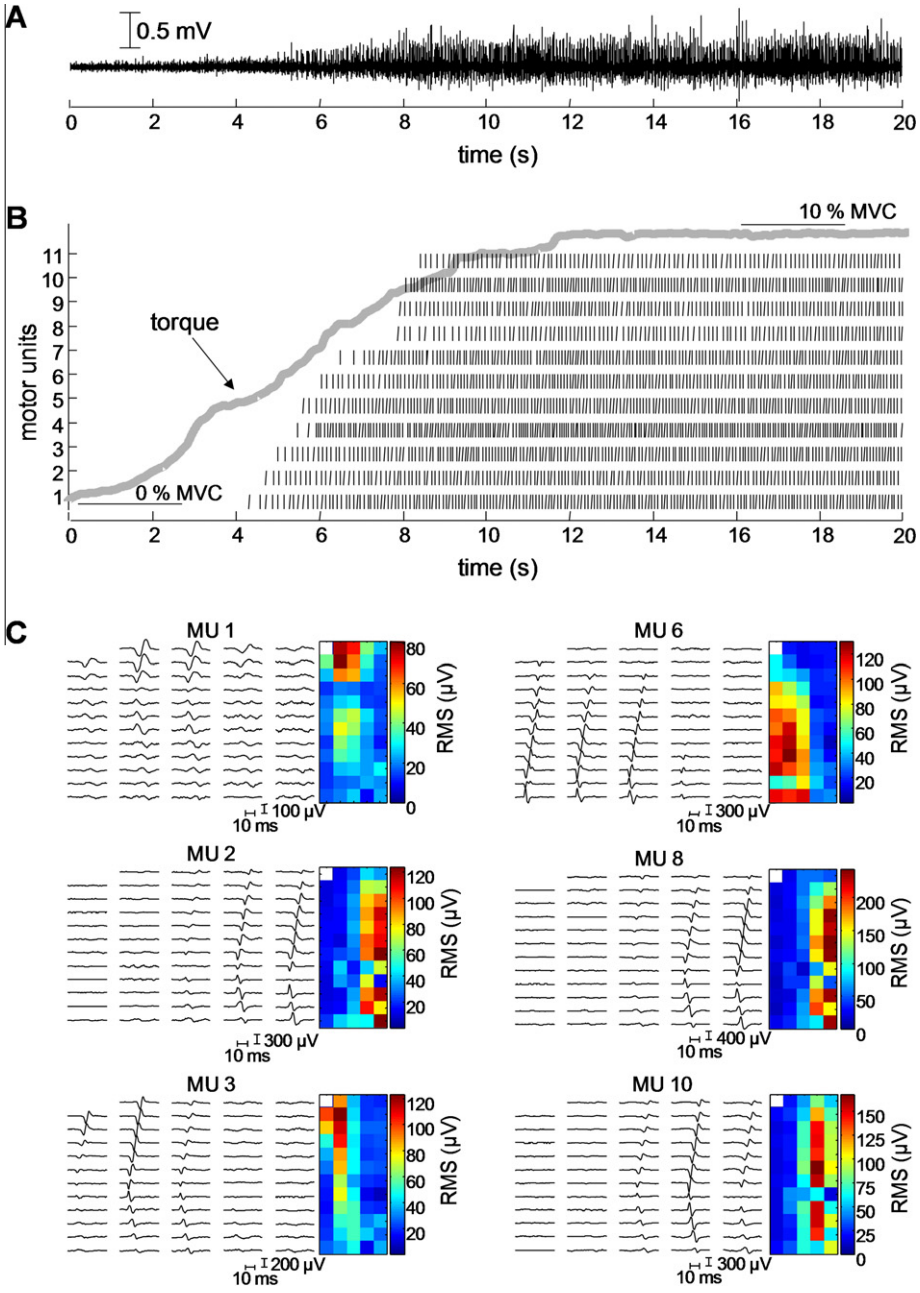

Fig. 4. (A) One channel of surface EMG recorded from the biceps brachii muscle of a healthy man during a linear increase in force from 0% to 10% of the maximal voluntary contraction (MVC) force in 10 s, followed by holding the 10% MVC force for 10 s. The surface EMG was recorded with a grid of 5 × 13 electrodes (8 mm interelectrode distance) and was decomposed with the method proposed by Holobar and Zazula (2007). (B) Discharge times of 11 motor units that were identified from the decomposition of the surface EMG. (C) The multi-channel action potentials for six representative motor units out of the 11 identified, as averaged over all the discharge times of each unit. The amplitude values (RMS) for each channel (5 × 13) are also reported on the right of each action potential. The action potentials for these motor units all differed from each other based on shape and location. MU, motor unit.

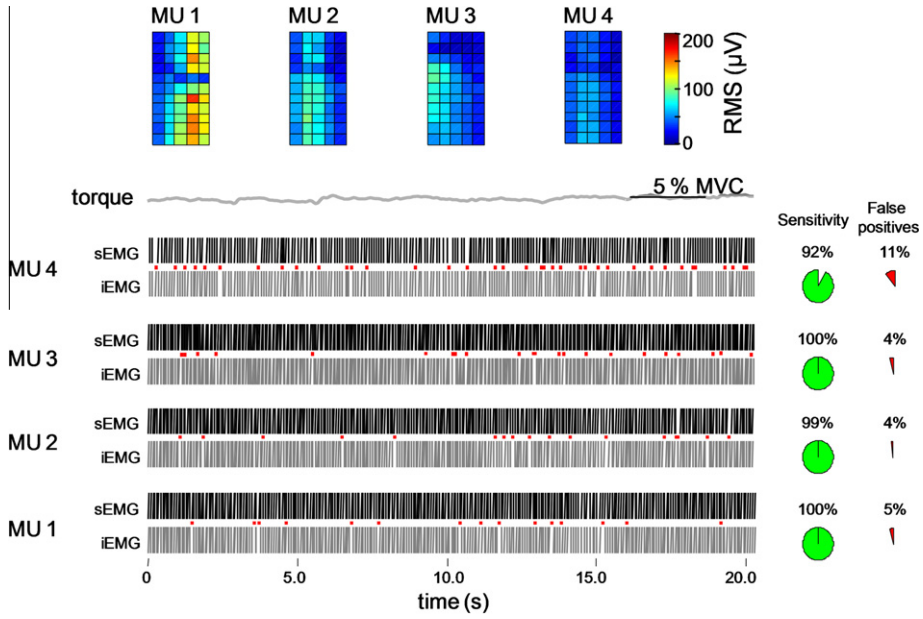

Fig. 5. Surface and intramuscular EMG signals were concurrently recorded from the abductor digiti minimi muscle of a healthy man during an isometric contraction at 5% of the maximal voluntary contraction (MVC) force. Surface EMG was detected with a grid of 5 × 13 electrodes (3 mm interelectrode distance) and intramuscular EMG by two pairs of wire electrodes. The recordings were decomposed with the methods described by McGill et al. (2005) (intramuscular EMG) and by Holobar and Zazula (2007) (surface EMG). Four motor units were detected by both the surface (sEMG) and the intramuscular EMG (iEMG) and the estimated discharge times were compared for the two decomposition methods. The red tic marks indicate the discharge times identified by one of the two EMG techniques but not by the other (disagreement in the decomposition). The sensitivity of surface EMG decomposition (reported on the right) was computed for each motor unit as the number of discharge times identified by both surface and intramuscular EMG decomposition divided by the total number of discharges identified from the intramuscular EMG. The percent of false positives was computed as the number of discharges identified by the surface but not by the intramuscular EMG decomposition divided by the total number of discharges identified from the intramuscular EMG. The amplitude maps of the surface action potentials of the four motor units are shown above the discharge-time traces. MU, motor unit.

signals indicated a similar accuracy with the decomposition for the two recordings during low-force isometric contractions (Fig. 5). For example, the proportion of discharge times identified in common by the decomposition of concurrently recorded intramuscular and surface EMG signals was >90% for contraction forces ranging between 2.5% and 20% MVC force in the abductor digiti minimi, tibialis anterior, and biceps brachii muscles (Holobar et al., 2010). Moreover, it has been shown that the muscle architecture does not impact the quality of the EMG decomposition (Merletti et al., 2008) and that high-density EMG decomposition methods have potential clinical applications (e.g., Kleine et al., 2008).

4. Representativeness and accuracy

The number of motor units that can be identified with decomposition of the surface EMG varies substantially across subjects, muscles, and conditions. For example, the range of individual motor units detected from the abductor digiti minimi, tibialis anterior, and biceps brachii muscles during static contractions at ⩽10% MVC force was 1–19 (Holobar et al., 2010). Simulation analyses indicate that the proportion of motor units identified by surface EMG decomposition is usually small when compared with the number of active motor units. Fig. 6 shows the motor units identified by the decomposition of a simulated surface EMG signal. In this example, approximately 23% of the active units were identified and smaller percentages were obtained for higher contraction forces. Sample size is usually smaller with invasive methods, which can impede generalizations about motor unit function (Tracy et al., 2005). Despite the relatively few motor units that can be identified by decomposition of the surface EMG, the electrical activity of the identified motor units explains most of the interference signal (Fig. 6B). This finding indicates that the amplitude of the surface

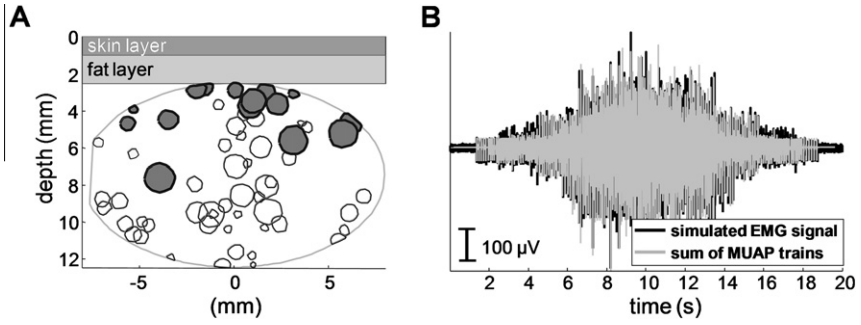

Fig. 6. (A) Simulated territories of active motor units in a muscle. Surface EMG signals generated by motor units were simulated with the planar volume conductor model described by Farina and Merletti (2001) and the motor unit recruitment model described by Fuglevand et al. (1993). The model parameters were the same as in Keenan et al. (2005) and the simulated signal-to-noise ratio was 20 dB. The EMG signals were generated during a linear increase and then decrease in force from 0% to 10% of the maximal force and were detected with a grid of 5 × 13 electrodes with 3.5 mm interelectrode distance in both directions (bipolar derivations). The territories of the motor units identified by the decomposition method are indicated as filled circles in (A) and constitute ∼23% of the active population. (B) The sum of the identified motor unit action potential trains (grey line) compared with the signal derived from all the active motor units (black line). The simulated noise level corresponds to 20 dB of signal-to-noise ratio. MUAP, motor unit action potential. Redrawn with permission from Holobar et al. (2009).

EMG does not represent the activity of a substantially larger number of motor units than it is possible to identify through decomposition. Furthermore, both amplitude and EMG decomposition are biased towards the motor units with the largest surface action potentials, i.e., large and superficial motor units.

Although both surface EMG amplitude and EMG decomposition provide a limited representation of muscle activity and EMG amplitude is a less accurate identification of the neural activation, the decomposition of surface EMG is currently limited to low contraction forces and to isometric conditions. These limitations do not apply to the analysis of neural activation with surface EMG amplitude that can be easily performed in any conditions.

Due to the relatively few motor units that are identified with decomposition of the surface EMG, the number of motor neuron discharges is less than the output from the spinal cord. Moreover, it is not possible to estimate the deficit in the estimation of number of discharges as this depends on factors that cannot be measured or predicted. Consequently, it is not currently possible to obtain an absolute measure of the neural drive to the muscle by decomposition of the surface (or intramuscular) EMG, even at low contraction forces. Nonetheless, relative changes in neural drive can be estimated from the limited sample of motor units if the behavior of the detected units is representative of the population; that is, if the information contained in the ensemble of discharge patterns has low dimensionality (Negro et al., 2009).

Because the descending and sensory inputs diverge onto alpha motor neurons (Lawrence et al., 1985; Ishizuka et al., 1979), there is some correlation between the low-frequency oscillations in motor neuron discharge rates (De Luca et al., 1982). The low-frequency oscillations in the motor output from the spinal cord can often be described by a low-dimensional signal extracted from the correlated activity of relatively few motor neurons (Negro et al., 2009). For this reason, the number of action potentials discharged per second by relatively few units in Fig. 1 was well correlated with the force (Fig. 1C) and thus representative of the entire active population. Fig. 7 shows a representative analysis of the dimensionality of the multivariate smoothed discharge rates of 10 motor units in the abductor digiti minimi muscle during an isometric contraction at 10% of the maximal force. In this example, one signal represented most of the variance (>70%) in the set of low-pass filtered discharge rates.

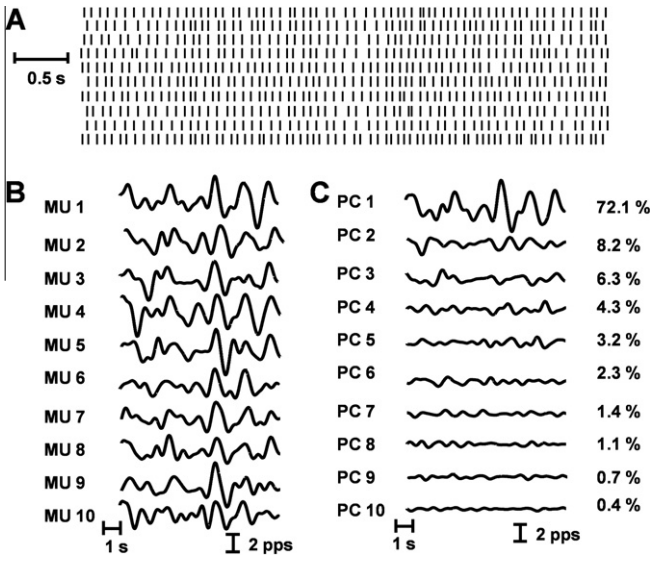

Fig. 7. (A) Discharge times for 10 motor units identified in surface and intramuscular EMG recordings from the abductor digiti minimi muscle during a contraction at 10% of the maximal force of 10 s. (B) Smoothed discharge rates were obtained for the 10 motor units by filtering the point process representing the inverse of the interspike intervals (Hann window of 400 ms duration and high-pass filtering at 0.75 Hz to remove the mean value). (C) Principal components extracted from the smoothed discharge rates shown in (B). The procedure for this analysis is described in Negro et al. (2009). The percent of variance of the smoothed discharge rates explained by each principal component is reported on the right. The first component explained most of the variance. MU, motor unit; PC, principal component.

Despite the possibility of inferring changes in the neural activation (mainly low-frequency components) from relatively few motor units in some conditions (Fig. 7), more subtle adjustments in motor neuron properties cannot be described as common changes in a population. For example, the changes in recruitment thresholds and discharge rate during intermittent fatiguing contractions differ substantially among low-threshold motor units (Farina et al., 2009). These changes cannot be inferred from only a limited number of units and require a larger sample. Moreover, the strength of correlation in low-frequency components of motor neuron discharges may vary across muscles (De Luca and Erim, 1994). Currently, there are no validated methods that can identify most of the active motor units in vivo during a voluntary contraction.

5. Conclusion

Surface EMG has been classically used to estimate the neural activation sent from the spinal cord to muscle by associating its amplitude to the number of action potentials discharged by a population of motor neurons. Although this approach is valuable in some applications, the amplitude of the surface EMG is a relatively crude index of neural drive and does not detect small fluctuations in motor unit activity or adjustments during fatiguing contractions. One of the major advances in surface EMG processing in recent years is the development of techniques to identify the discharge times of individual motor units from the interference signal, with an accuracy that is similar to invasive methods. This approach, however, is limited to isometric contractions and to low forces, in contrast to the more widespread applications of surface EMG recordings. An additional limitation of EMG decomposition is that it identifies only a small proportion of the active units and these tend to be located superficially in the muscle. Despite these limitations, surface EMG decomposition allows the accurate detection of relative changes in neural activation. As it seems unlikely that surface EMG methods can be used to identify deep motor units, a complete decoding of the neural drive to muscle in vivo will likely require joint multi-channel intramuscular and surface EMG recordings (Farina et al., 2008c; Holobar et al., 2010).

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